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BACHELOR THESIS

Forecasting Capability of the GDP Components: Granger Causality Approach

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

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Signature

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Abstract

This work aims to provide with the procedure of bivariate causality testing based on Granger (1969). We focused on exploration of forecasting capability of GDP components on output itself. We examine, which of five components defined in accordance with the expenditure approach can be useful in forecasting economic growth. Overall, the causal relationship is examined on national accounts data from three member states of the European Union: Austria, France and Germany. For the sake of general inference, the Granger causality tests are executed on panel data, too. We concluded, that consumption and investment possess ability to forecast economic growth. In contrast, GDP was found to be useful in forecasting government expenditures.

JEL Classification	C22, C23, C51, E20, N10
Keywords	Granger Causality, GDP, expenditure approach, forecasting, predictions, Akaike information criterion (AIC), Bayesian information criterion (BIC)

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Abstrakt

Tato práce je zaměřena na testování Grangerovy kauzality dvou proměnných. Naším cílem je určení prognostické síly komponentů HDP, které jsou definovány na základě výdajové metody. Celkově zkoumáme, který z komponentů je využitelný pro předpovídání hospodářského růstu. Za účelem naší empirické studie jsme se rozhodli určovat kauzální vztahy mezi proměnnými národních účtů na datech tří členských států Evropské unie: Francie, Německa a Rakouska. Pro obecnější empirický úsudek je navíc vytvořena panelová databáze. Zjistili jsme, že zatímco spotřeba a investice jsou užitečné k předpovídání hospodářského růstu, samotný HDP vlastní prognostickou sílu na vládní výdaje.

Klasifikace JEL	C22, C23, C51, E20, N10
Klíčová slova	Grangerova kauzaliza, HDP, výdajová metoda, prognózy, predikce, Akaikeho informační kritérium, Bayesovo informační kritérium

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Acronyms

ADF Augmented Dickey-Fuller

DF Dickey-Fuller

FD First-difference

FDL Finite distributed lag

GDP Gross domestic product

I(0) Integrated of order zero

I(1) Integrated of order one

i.i.d. Independent and identically distributed

OLS Ordinary least squares

VAR Vector autoregression

VEC Vector error correction

Bachelor Thesis Proposal

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Proposed topic	Forecasting Capability of the GDP Components: Granger Causality Approach

Topic characteristics This work aims to provide with the procedure of bivariate causality testing based on Granger (1969). We focus on exploration of forecasting capability of GDP components on output itself. We examine, which of five components defined in accordance with the expenditure approach can be useful in forecasting economic growth.

Hypotheses Generally, the aim of the thesis is to determine the causal relationship between the variables defined in accordance with the expenditure approach of GDP calculation:

$$Y = C + I + G + X - M$$

Overall, we are interested which of five independent variables are useful in forecasting output. In addition, the forecasting capability of GDP on its components is examined, too.

Methodology For the purpose of an empirical analysis, we collected data of three countries of the European Union (Austria, France and Germany) which were subjects of the Granger causality tests. The bivariate causal relationship is examined on either VAR(n) model in log-differences or VEC(n) model, where n stands for the number of time lags selected either Akaike information criterion and Bayesian information criterion.

Outline

1. Introduction
2. Literature review
3. Theoretical background
4. Empirical study
5. Conclusion

Core bibliography

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Chapter 1

Introduction

Till the second half of the 20th century scholars mostly viewed causality as a question of philosophy. Nevertheless, in the year 1969 Granger introduced his study in which he focused on the more operational definition of causality. As a result, scholars gained an exact procedure how to study the issue of cause and consequence from the empirical point of view. Overall, based on the observed causal relationship between two variables we can draw a conclusion about their forecasting capability on each other. (Granger 1969)

The objective of this thesis is to explore causal relationship between real GDP and its component variables. The component variables are determined in accordance with the expenditure approach of output calculation, which Mankiw (2010) defines as follows: $Y = C+I+G+X-M$, where C stands for household consumption, I for investment, G for government expenditures, X for gross export and M for gross import. In general, we are going to devote to the forecasting capability of these five components on GDP itself.

This thesis is structured in the following way: in the chapter 2 we are going to devote to the review of philosophers and economists who studied the question of cause and consequence. The chapter terminates with recapitulation of Granger's point of view and its use among other researchers. In the chapter 3 we are going to elucidate the background for the Granger causality test. The chapter 4 introduces the advanced tests, so that the best fitting model can be constructed. In the chapter 5 we elaborate our own empirical study based on the literature and methodology mentioned in the previous chapters. The chapter 6 summarizes our findings.

Chapter 2

Causality

2.1 History

The proper definition of causality has been widely discussed by a lot of scholars. Some of them agree that the roots of studying the issue of causality can be traced back to Classical Greece. In that time, philosopher Aristotle introduced his approach to cause and consequence. However, currently his opinions are considered to be complicated and extensive. (Granger 1980; Hoover 2008; Korda 2007)

Therefore, causality was firstly viewed purely from philosophical and theoretical perspective. Nevertheless, famous philosopher Hume (18th century) started to perceive concepts of cause and consequence from the empirical point of view. He claimed that if two processes are related and the relation is observable over time, human mind is able to determine which of these processes are characterized as cause and which as consequence (Korda 2007; Maziarz 2015). Hence, it was a crucial point in the perception of causality. Furthermore, Hoover (2008, p.1) states that Hume *"set the tone for much of the later development of causality in economics"*.

After Hume a lot of other philosophers/economists (e.g. Smith, Ricardo and Mill) devoted to the question of causality (Maziarz 2015). However, for the purpose of potential statistical research, their spectrum of definitions proved to be irrelevant (Granger 1980).

Korda (2007) explains the difference between philosophical and empirical conception of causality. He points out that economic phenomena are based on decisions of individual units — people. For that reason, original causes (and consequences) are always driven by separate decisions of individuals. Obviously, human's behaviour is unpredictable and unstable, therefore it is necessary to transfer economic causes (and consequences) to better observable aggregates. Consequently, economists have been trying to find a way to measure causality with the aid of some representative model, which would assemble all unobservable factors into complex set of assumptions.

2.2 Granger causality

In the year 1969 Granger introduced his Nobel Prize awarded study in which he proposed the most operational definition of causality till that time (Granger 1969; 1980; Xu 2015). As a result, his method has become largely used in many fields, especially in economics and econometrics, but also in other fields like neurosciences and epidemiology (Maziarz 2015; Xu 2015). Maziarz (2015) found, that the Granger causality has grown in popularity almost exponentially in the beginning of the 21st century. The author demonstrates that the number of published academic papers, with "Granger causality" included in the key words, grew between years 2001 and 2011 more than six times. He explains this increasing popularity by the fact that statistical software packages have been becoming constantly more and more accessible. To summarize, Hoover (2008, p.12) described the Granger's method as *"the most influential explicit approach to causality in economics"*.

2.2.1 Review of Granger causality

As mentioned before, Granger endeavoured to deal with the lack of proper definitions of causality. For the case of simplicity, he assumed only two variables X and Y being included in the universe. Naturally, the unequivocal question arises immediately: whether X causes Y ($X \rightarrow Y$) or Y causes X ($Y \rightarrow X$). What is more, there is also possibility that the effect is reciprocal or alternatively these two variables are generally not causally related. (Granger 1980)

Nevertheless, he emphasized that many textbooks and scholars had never proposed an efficient procedure for causality testing. The lack of the procedure was obviously due to absence of a definition which would be generally accepted (Granger 1980). Moreover, he also attempted to overcome the issue of incorrectly related terms "correlation" and "causation" which is generally viewed as the biggest misdemeanour of statisticians (Maziarz 2015). In order to set the tone for further procedure of causality testing, Granger (1980, p.330–335) defined three axioms.

Axiom A : "The past and present may cause the future, but the future cannot cause the past."

Axiom B : "Ω_n contains no redundant information, so that if some variable Z_n is functionally related to one or more other variable, in a deterministic fashion, then Z_n should be excluded from Ω_n." The symbol Ω_n denotes all information contemporary included in the universe and n is a time index.

Axiom C : "All causal relationships remain constant in direction throughout time."

During the ceremony speech after he had been given the Nobel Prize, he admitted that the origins of the axioms were influenced by Hume's ideas. Furthermore, he pointed out that the final settlement of the already mentioned problem of misinterpreted correlation and causality is encompassed in the third axiom (Maziarz 2015).

For the sake of simplicity, Granger (1980) demonstrated his ideas in a real-life example. Imagine that the universe contains three time series variables: first variable is the number of patients arriving at a hospital, second is the number of patients abandoning the hospital and finally third variable is the amount of ice cream sold in the nearest town that day. Undoubtedly, the correlation between the second and the third variable may surface during short period of time, however there is no point in assuming that they are internally related in long run.

Nevertheless, difficulty in describing behaviour of exact cause and consequence of two variables still comes into question. Even if we would know that a variable X causes a variable Y, it is still impossible to create a general and structural pattern for proper statistical inference. For that reason, Granger (1980) mentions another real-life example. For now, imagine only two variables: a smoker and a cancer. An economist would be most likely reluctant to assert that a smoker will definitely contract a cancer. Nonetheless, the claim that smoking increases the probability of getting cancer would be presumably accepted. Hence, the simple idea of the probabilistic causality can be defined in the following statement: An event A is caused by an event B if and only if the event B occurred before A and probability of A conditional of B is higher that probability of A alone, mathematically depicted as $\Pr(A \mid B) > \Pr(A)$.

2.2.2 Granger causality among researchers

The increase in popularity of the Granger's study resulted in variety of released academic papers discussing this topic. We are going to mention the researches where scholars aimed to explore causal relations among main macroeconomic variables. In particular, GDP and related economic growth with respect to national account data are frequently in the spotlight of academic surveys.

Tiwari (2014) explored causal relationship between income and components of energy consumption within the US economy. He concluded, that coal consumption is Granger-caused by GDP, in contrast GDP is Granger-caused by total electricity consumption. As for the other components, e.g. natural gas consumption, total renewable energy consumption and primary energy consumption, the explored causality was found to be reciprocal. In addition, Narayan & Smyth (2008) exemplify the relation between real GDP and real energy consumption within a panel dataset containing G7 countries. They found evidence for real GDP being Granger-caused by real consumption. Furthermore, the authors estimated the long-run elasticity effect between these two variables. They demonstrated that permanently raising real energy consumption by 1% results in 0.12% – 0.39% increase in real output.

Regarding another studies based on the Granger's methodology, Green (1997) explored whether residential and non-residential investment of the US economy are efficient to predict economic growth. As a result, he concluded that residential investment incorporates predictive capability on GDP, whereas non-residential is estimated to be predicted by GDP. Furthermore, Kumar Narayan & Smyth (2006) studied the causal relationship between real investment and real GDP with respect to large Chinese economy. The authors found evidence that real investment is Granger-caused by real output.

In consideration of another national account variable, government expenditures were subject to the Granger causality research performed with respect to South Korean data (Cheng & Lai 1997). As for the methodology, the authors used a VAR model to determine the nature of causality between income and expenditures. When it comes to results, they concluded that these two variables are influenced mutually.

Next, Ming-Hsien *et al.* (2015) were examining the causal relationship between export and economic growth. With the aid of a VAR model they concluded that export is Granger-caused by GDP and vice versa, hence the relation is reciprocal. In addition, Todshki & Ranjbaraki (2016) executed a resembling research within the Iranian economy. Similarly, the authors found the evidence for steel export and output being affected mutually. What is more, they ascertained that income Granger-causes steel import.

Chapter 3

Testing for Granger causality

The basic idea of the original Granger causality test is very simple. Assume two stochastic processes x_t and y_t. It is said that variable x_t Granger-causes variable y_t if and only if lagged values of both y_t and x_t have better forecasting capability on y_t than just lagged values of y_t on itself. The testing method is based on OLS regressions and is executed in the following way.

Firstly, we define the following equations:

$$y_t = a_0 + \sum_{i=1}^{n} b_{1,i} y_{t-i} + u_{1,t}, \tag{3.1}$$

$$y_t = a_1 + \sum_{i=1}^{n} b_i y_{t-i} + \sum_{i=1}^{n} c_i x_{t-i} + u_t, \tag{3.2}$$

where u_t and $u_{1,t}$ are i.i.d. error terms, a_0 and a_1 are constants, $b_{1,i}$, b_i and c_i for $i = 1...n$ are coefficients.

Secondly, we calculate sum of squared residuals of both equations 3.1 and 3.2:

$$SSR_1 = \sum_{t=1}^{N} \hat{u}_{1,t}^2, \tag{3.3}$$

$$SSR_2 = \sum_{t=1}^{N} \hat{u}_t^2. \tag{3.4}$$

Thirdly, we determine the test statistics as follows:

$$T = \frac{\frac{SSR_1 - SSR_2}{n}}{\frac{SSR_2}{N-2n-1}}, \tag{3.5}$$

where N is the sample size and n represents the number of lags. The test statistics has asymptotically $F(n, N-2n-1)$ distribution.

Fourthly, we are interested in the null hypothesis of no Granger causality:

$$H_0 : c_i = 0, i = 1...n.$$

If we reject the null hypothesis at a certain level of significance, then we conclude that the variable x_t Granger causes the variable y_t, therefore x_t has capability to forecast y_t (Xu 2015).

For the purpose of proper statistical inference, all of the variables included in the regression must be stationary (Green 1997; Wooldridge 2013). If variables are driven by a deterministic process (a time trend), the coefficients will be biased and therefore the further statistical inference will be incorrect. Generally, a lot of economic time series are non-stationary because of a time trend (Wooldridge 2013). Hence, some authors (Green 1997; Guilkey & Salemi 1982) include a time variable into the equation 3.2, which is then rewritten as the equation 3.6:

$$y_t = a_3 + \sum_{i=1}^{n} b_{3,i} y_{t-i} + \sum_{i=1}^{n} c_{3,i} x_{t-i} + dt + u_{3,t}, \tag{3.6}$$

where $u_{3.t}$ is i.i.d. error term, a_3 is a constant, d, $b_{3,i}$ and $c_{3,i}$ for $i = 1...n$ are coefficients and t is a time variable. Wooldridge (2013) considers the latter as one of the main detrending procedures.

3.1 VAR model

As mentioned before, the variable x_t has predictive power on variable y_t if and only if lagged values of both y_t and x_t have better forecasting capability on y_t than just lagged values of y_t on itself. Thus, it is necessary to construct model which would contain information from past and moreover the information would be included among regressors — on the right hand side of the equation.

The simplest example of such model is an univariate autoregression of order n. In this case, we regress a variable on itself and the regressors will contain past information included in n lags. On the contrary, if more variables are incorporated on the right side of an equation then we call it a multivariate autoregression. In this thesis we are going to frequently use the term vector autoregression (VAR). N-multivariate VAR(n) model (called vector autoregressive model of order n) contains n lags of N variables. Furthermore, it is estimated by N equations (Diebold 1998). For the sake of clarity, N-multivariate VAR(n) is a set of N models, where the right side remains N times the same. Nevertheless, dependent variable is always different. Specifically, N times different.

For instance, equation 3.2 is one part of bivariate VAR(n). Second part will be defined as follows:

$$x_t = a_2 + \sum_{i=1}^{n} b_{2,i} y_{t-i} + \sum_{i=1}^{n} c_{2,i} x_{t-i} + u_{2,t}, \tag{3.7}$$

where $u_{2,t}$ is i.i.d. error term, a_2 is a constant, $b_{2,i}$ and $c_{2,i}$ for $i = 1...n$ are coefficients. For the purpose of original Granger causality testing, only bivariate VAR will be used in the thesis.

3.2 Incorrect statistical inference

Notwithstanding the fact that Diebold (1998, p.476) describes the VAR approach as *"simple and stable"* and to have *"very good statistical properties"*, some authors emphasize the danger misinterpreted inference (Green 1997; Iqbal & Uddin 2013; Maziarz 2015). Generally, there are several undesirable factors which have to be dealt with.

3.2.1 Non-stationarity

Firstly, time series can be non-stationary, meaning that their mean value is not constant over time. As already mentioned, the basic cause of non-stationarity is a time trend. Series such as GDP naturally grow over time which causes the mean value to fluctuate around a time trend. Another case of non-stationarity is when stochastic processes have a unit root or equivalently defined — stochastic processes are I(1). Otherwise, they are stationary I(0) processes (Wooldridge 2013).[1]

Time series, which are I(1), evince strong correlation among all variables over time. For the sake of clarity, one variable at time t contains information which strongly affects variables at time $t+1$, $t+2$ or $t+h$ in general (Wooldridge 2013).

[1] I(0) and I(1) time series are called integrated of order zero, or integrated of order one processes. Sometimes a stochastic process is I(2), but for the purpose of this thesis the definitions of I(1) and I(0) processes will be sufficient.

3.2.2 Differencing

Wooldridge (2013) proposes several ways to deal with non-stationary time series. As mentioned above, including a time trend among independent variables handles with biasedness of coefficients. However, the underlying stochastic processes will still remain non-stationary. What is more, this method is useful only if time series are I(0).

As for a real dataset, a stochastic process might happen to be both I(1) and time trending, too. On the whole, scholars usually recommend one simple procedure to create stationary time series (Green 1997; Maziarz 2015; Wooldridge 2013). The fluctuating mean value of a time series is stabilized by so called differencing, which is intuitively done in the following way:

$$\Delta x_t = x_t - x_{t-1}.$$

Overall, if a time series, which is time trending and has a unit root, is put into differences, the resulting stochastic process is integrated of order zero (Wooldridge 2013).

3.2.3 Cointegration

Bivariate VAR(n) models in differences (for example 3.8 and 3.9) are widely used by econometricians for the purpose of Granger causality testing (Green 1997; Iqbal & Uddin 2013).

$$\Delta y_t = \alpha_1 + \sum_{i=1}^{n} \beta_{1,i} \Delta y_{t-i} + \sum_{i=1}^{n} \gamma_{1,i} \Delta x_{t-i} + \varepsilon_{1,t}, \tag{3.8}$$

$$\Delta x_t = \alpha_2 + \sum_{i=1}^{n} \beta_{2,i} \Delta y_{t-i} + \sum_{i=1}^{n} \gamma_{2,i} \Delta x_{t-i} + \varepsilon_{2,t}, \tag{3.9}$$

where $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ are i.i.d. error terms, α_1 and α_2 are constants, $\beta_{1,i}$, $\beta_{2,i}$, $\gamma_{1,i}$ and $\gamma_{2,i}$ for $i = 1...n$ are coefficients.

Nonetheless, Green (1997) argues that the underlying statistical inference is falsely concluded if both variables are so called cointegrated. Two time series can be cointegrated if and only if both are I(1) processes. Naturally, their linear combination can be also I(1) process, however it does not have to be necessarily. If a linear combination of two stochastic processes is integrated of order zero then the time series are cointegrated. For the sake of clarity, cointegration means that a linear combination of two non-stationary processes is stationary, hence has a constant mean and variance (Wooldridge 2013).

As for a less technical description, two cointegrating processes have an inner long run relationship. For instance, cointegrated variables x_t and y_t will move over time in a similar way. What is more, the movement is to some extend predictable. In other words, linear combination of x_t and y_t will not deviate far from its long-run equilibrium. (Wooldridge 2013)

On the whole, if two time series variables are cointegrated, a bivariate VAR model in differences will show incorrect evidence about Granger causality. Some scholars contend that cointegration of two variables in a bivariate VAR model can be dealt with adding an error-correction term (Green 1997; Iqbal & Uddin 2013; Maziarz 2015). Therefore, the bivariate VAR model 3.8 and 3.9 will be modified as follows:

$$\Delta y_t = \alpha_3 + \sum_{i=1}^{n} \beta_{3,i} \Delta y_{t-i} + \sum_{i=1}^{n} \gamma_{3,i} \Delta x_{t-i} + \delta_3 (y_{t-1} + \eta_3 - \mu_3 x_{t-1}) + \varepsilon_{3,t}, \quad (3.10)$$

$$\Delta x_t = \alpha_4 + \sum_{i=1}^{n} \beta_{4,i} \Delta y_{t-i} + \sum_{i=1}^{n} \gamma_{4,i} \Delta x_{t-i} + \delta_4 (y_{t-1} + \eta_4 - \mu_4 x_{t-1}) + \varepsilon_{4,t}, \quad (3.11)$$

where $\varepsilon_{3,t}$ and $\varepsilon_{4,t}$ are i.i.d. error terms, α_3 and α_4 are constants, $\beta_{3,i}$, $\beta_{4,i}$, $\gamma_{3,i}$ and $\gamma_{4,i}$ for $i = 1...n$ are coefficients and $\delta_l(y_{t-1} + \eta_l + \mu_l x_{t-1})$ for $l = 3, 4$ are called error-correction terms and represent the linear relationship between x_t and y_t. The set of equations 3.10 and 3.11 is called a bivariate vector error-correction (VEC) model. (Wooldridge 2013)

3.2.4 Number of lags

The number of lags in either VAR or VEC model will have an important impact on the conclusion from the Granger causality test. Naturally, the more lags included among independent variables the more past information is available for determining the value at time t. As a result, there are several approaches to specify the number of lags.

Green (1997) mentions two techniques for determining the length of a series of past values in a model. Firstly, the author declares that according to a previous empirical research the optimal number of lags is six. Therefore, the dependent variable will be explained by variables containing information of previous six periods.

Secondly, he suggests another method which he called *"allow the data to* *speak"* (Green 1997, p.255). Technically speaking, the optimal number of lags is selected according to F-test of joint significance and t-test for individual significance. As a practical example, a researcher will be adding independent variables into a model till they are significant both individually and jointly.

In addition, Iqbal & Uddin (2013), Maziarz (2015) and Xu (2015) point out another two widely used techniques for a lag determination. They mention that specifying number of lags should be based on Akaike information criterion (AIC) and Bayesian information criterion (BIC).

3.2.5 Forecasting versus predicting

In accordance with Granger (1980), the research of causality is viewed in terms of forecasting. What is more, Diebold (1998) proposes a VAR model as a precise subject for forecasts, since it is originally constructed for one-step ahead forecast. However, when it comes to Granger causality, (Diebold 1998, p.477) calls it *"predictive causality"*. In terms of predictions is also written by some other authors who devoted to the issue of Granger causality (Green 1997; Maziarz 2015).

Therefore, in this thesis there will be no such an emphasis put on the difference between predicting and forecasting. In that we are going to speak only about usefulness of one variable to cause another, the terms like forecasting capability, predictive capability, predictive power, forecasting ability etc. will be meant like synonyms.

Chapter 4

Advanced tests for the best fittting model

4.1 Information criteria

As already mentioned, some authors stress the importance of the AIC and BIC when it comes to a lag determination. Hence, we will demonstrate their performance on a dataset of real economic variables.

Criteria AIC and BIC are used for the purpose of a model selection. Acquah (2010), who investigated the performance of the criteria on asymmetrical data, mentions that both have recently grown in popularity.

Both AIC and BIC are constructed for searching the best fitting model among the set of beforehand chosen models. Several comparisons have been made and it was proved, that the AIC performs better in relatively small samples, while the BIC was more efficient in larger samples. What is more, due to being broadly used, the criteria are computed in most of statistical software packages. (Acquah 2010)

4.1.1 Akaike information criterion

Selecting procedure of the proper model is based on the following equation, which computes the AIC statistics:

$$AIC = -2\log L + 2p, \tag{4.1}$$

where log is natural logarithm, L is maximized likelihood function of the model and p is the number of parameters in the model.

We determine the best model according to the statistics in such a way that the AIC value is minimized. While the first negative variable of the equation 4.1 is in logical compliance with this determination process, the second variable pushes the overall AIC value to positive numbers. As a result, the p in the equation stands for penalization for the larger number of parameters. (Acquah 2010)

As an practical application, a researcher firstly chooses some models from which he or she would like to get the "winner". Then he or she computes the AIC statistic and the desirable model will be the one with the lowest AIC value.

4.1.2 Bayesian information criterion

Computation of the BIC statistics is based on the equation defined as follows:

$$BIC = -2 \log L + p \log N, \tag{4.2}$$

where log is natural logarithm, L is maximized likelihood function of the model, p is the number of parameters in the model and N is a sample size.

The practical application is the same as with the AIC before: the desirable statistics is the lowest one. However, there is a subtle difference in the interpretation of the positive penalty term. In addition to the AIC statistics, the coefficient depends on the sample size N.

4.2 Testing for a unit root

As mentioned before, non-stationarity of time series can result in incorrect conclusion about a model. Overall, if we regress trending variables on each other, the result will be so-called spurious regression (Wooldridge 2013). Therefore, it is vital to derive a test for stationarity.

Wooldridge (2013) proposes the technique for a unit root test. The procedure is based on auto-regression, when a variable is regressed on its past values. The basic test is called Dickey-Fuller (DF) test and the fundamental equation is defined in the following way:

$$\Delta y_t = \tau_1 + \theta_1 y_{t-1} + \epsilon_{1,t}, \tag{4.3}$$

where $\epsilon_{1,t}$ is i.i.d. error term, τ_1 is a constant and θ_1 is a coefficient. The null hypothesis of existence of a unit root is stated as follows:

$$H_0 : \theta_1 = 0$$

against the alternative hypothesis:

$$H_1 : \theta_1 < 0.$$

Naturally, rejecting the null implies that we have found some evidence of a stochastic process being I(0). (Wooldridge 2013)

However, if variables are driven by a deterministic trend, the result from the test will be biased. Hence, Wooldridge (2013) suggests that the test be extended by a time trend. As a result, the equation 4.3 will be redefined as:

$$\Delta y_t = \tau_2 + \theta_2 y_{t-1} + \lambda_2 t + \epsilon_{2,t}, \tag{4.4}$$

where $\epsilon_{2,t}$ is i.i.d. error term, τ_2 is a constant, θ_2 and λ_2 are coefficients and t is a time variable. As before, we are interested in the null hypothesis of $H_0 : \theta_2 = 0$ against its alternative $H_1 : \theta_2 < 0$.

In addition, Wooldridge (2013) describes tests for a unit root, which are broaden by more complex dynamics. For instance, the equations 4.3 and 4.4 can be augmented by lagged values of Δy_t:

$$\Delta y_t = \tau_3 + \theta_3 y_{t-1} + \theta_3^{ADF} \Delta y_{t-1} + \epsilon_{3,t}, \tag{4.5}$$

$$\Delta y_t = \tau_4 + \theta_4 y_{t-1} + \theta_4^{ADF} \Delta y_{t-1} + \lambda_4 t + \epsilon_{4,t}, \tag{4.6}$$

where $\epsilon_{3,t}$ and $\epsilon_{4,t}$ are i.i.d. error terms, τ_3 and τ_3 are constants, θ_2, θ_3 and λ_4 are coefficients and t is a time variable. The tests based on these equations are called Augmented Dickey-Fuller (ADF) tests. As for the hypotheses, they remain the same as in the tests 4.3 and 4.4.

Nevertheless, the t-statistics of the θ_i (for $i = 1, 2, 3, 4$) coefficient is not consistent with the Student's t-distribution. For that reason, Dickey and Fuller derived their own critical values which follows so called Dickey-Fuller distribution. The asymptotical critical values based on their calculation are -2.86 for the unit root test without a time trend and -3.41 with a time trend (5% significance level). (Wooldridge 2013)

4.3 Testing for cointegration

If the DF or ADF tests find (at a certain level of significance) no evidence for or against the null hypothesis, we conclude that the variables are I(1) processes. Nonetheless, we are interested in their linear combination, too. Two I(1) variables are cointegrated provided that their linear combination is stationary I(0) process. As a consequence of cointegration, the Granger's F-statistics is invalid. Therefore, Wooldridge (2013) proposes testing procedure based on a linear combination of two variables y_t and x_t:

$$y_t = \tau_5 + \theta_5 x_t + \epsilon_{5,t}, \tag{4.7}$$

$$y_t = \tau_6 + \theta_6 x_t + \lambda_6 t + \epsilon_{6,t}, \tag{4.8}$$

where $\epsilon_{5,t}$ and $\epsilon_{6,t}$ are i.i.d. error terms, τ_5 and τ_6 are constants, θ_5, θ_6 and λ_6 are coefficients and t is a time variable. If we conclude that the linear combination of these two stochastic processes is integrated of order zero, we call θ_i (for $i = 5, 6$) a *cointegrating* coefficient.

The difference between 4.7 a 4.8 is straightforward and follows the same principle as in DF tests, meaning that tests based on 4.8 are followed by time series which non-stationarity is caused by a time trend.

Nevertheless, testing for cointegration is more elaborate than original DF or ADF tests. While unit root can be determined by estimating simple regressions 4.3 and 4.4, the cointegration tests are more complicated since we firstly have to estimate the population parameter θ_i. Therefore, we firstly run a simple regression based on 4.7 or 4.8 from which we get the estimated parameter $\hat{\theta_5}$, or respectively estimated parameters $\hat{\theta_6}$ and $\hat{\lambda_6}$. Afterwards, we execute either DF or ADF test to residuals, which we have saved from the previous regressions. (Wooldridge 2013)

As a matter of an empirical study, the t-statistics is not consistent with the Student's t-distribution. What is more, the asymptotical critical values of standard DF or ADF will be inconsistent, too. The inconsistency is due to estimation of two regressions instead of just one, as is followed in DF or ADF tests. Therefore, the asymptotical critical values are -3.34 without a time trend and -3.78 with a time trend (5% significance level). The cointegration test based on this critical values is named the Engle-Granger test. (Wooldridge 2013)

4.4 Granger causality tests in panel data

Hoffmann *et al.* (2005), who explored Granger causality between pollution and foreign direct investment, claim that executing the Granger causality test on a panel improves its effectiveness. There are several advantages of creating a panel dataset. Obviously, via a panel we receive more observations, hence more information. Furthermore, by obtaining a panel dataset, we extend an information across observed variables, too. Overall, we increase a dataset in both length and cross-sectional dimensions (Hoffmann *et al.* 2005; Wooldridge 2013). Hoffmann *et al.* (2005) define a VAR model with respect to panel data as follows:

$$y_{i,t} = \alpha_5 + \sum_{i=1}^{n} \beta_{5,i} y_{k,t-i} + \sum_{i=1}^{n} \gamma_{5,i} x_{k,t-i} + a_{5,k} + \varepsilon_{5,k,t}, \tag{4.9}$$

where $\varepsilon_{5,k,t}$ is i.i.d. error term, α_5 is a constant, $\beta_{5,i}$ and $\gamma_{5,i}$ for $i = 1...n$ are coefficients, k determines the number of cross-sectional individuals and $a_{5,k}$ is so called *fixed effect* or *unobserved effect*.

The fixed effect $a_{5,k}$ contains the information which is stable over time and is specific for each k. As a specific example, if k stands for countries, then $a_{5,k}$ is an unobserved factor containing an information which is typical for the particular country. Nevertheless, the fixed effect is for $k > 1$ correlated with other independent variables. As a consequence, the correlation would cause biasedness of the coefficients and hence incorrect statistical inference. (Wooldridge 2013)

Thus, the unobserved effect needs to be controlled for. Wooldridge (2013) suggests the first differencing as one way of avoiding the heterogeneity bias[1]. The differenced VAR(n) will be defined as follows:

$$\Delta y_{i,t} = \alpha_6 + \sum_{i=1}^{n} \beta_{6,i} \Delta y_{k,t-i} + \sum_{i=1}^{n} \gamma_{6,i} \Delta x_{k,t-i} + \Delta\varepsilon_{6,k,t}, \tag{4.10}$$

where $\Delta\varepsilon_{6,k,t}$ is i.i.d. error term, α_6 is a constant, $\beta_{6,i}$ and $\gamma_{6,i}$ for $i = 1...n$ are coefficients, k determines the number of cross-sectional individuals. The estimation of the equation 4.10 is called first-difference (FD) estimator. Overall, under the FD estimator the statistics 3.5 is asymptotically valid.

Levin *et al.* (2002) introduced a version of a unit root test for panel data.

[1]bias due to correlation of the unobserved effect with other independent variables

Generally, the test is based on the regular DF test, however with further assumptions and improvements added for panel datasets. Generally, the test can be executed by most of the statistical software packages.

Chapter 5

Empirical study

5.1 Gross Domestic Product

Gross domestic product (GDP) measures the aggregate amount of goods and services within an economical unit, mostly a state. In most of the macroeconomic books is GDP denoted as Y. In general, there are many ways to compute the amount of total goods and services. The commonly proposed approach is so called *Expenditure Approach* and is defined as follows:

$$Y = C + I + G + X - M, \tag{5.1}$$

where C stands for household consumption, I for investment, G for government expenditures, X for gross export and M for gross import. (Mankiw 2010)

As mentioned at the beginning, in the thesis we are going to devote to the forecasting capability of these five components on GDP itself.

5.1.1 Dataset

The data for this research were downloaded from the website of Penn World Table (Feenstra *et al.* 2015). The site is very complex source of national accounts data. For the purpose of the thesis, we collected national accounts data of three countries of the European Monetary Union: Austria, France and Germany. Naturally, the collected national accounts are in the Euro currency. The obtained datasets contain five real economic variables in accordance with the GDP expenditure approach. The base year is set to be 2005 and the time series contain variables from 1950 to 2011, which results in 62 observations for each of the components. The data were processed in the statistical software package Stata 12.

5.1.2 Log-transformation

As mentioned before, the log-transformation is by econometricians commonly used method. Therefore, we put all of the variables into natural logarithm. The resulting denotation will be in the following way: $y_t = \log Y_t$, $c_t = \log C_t$, $i_t = \log I_t$, $g_t = \log G_t$, $x_t = \log X_t$ and $m_t = \log M_t$ for $t = 1950, 1951, ..., 2011$.

Nevertheless, for the purpose of non-stationarity and further Granger causality tests, the first-differencing needed to be executed, too. As a result, we define the following variables: $\Delta y_t = y_t - y_{t-1}$, $\Delta c_t = c_t - c_{t-1}$, $\Delta i_t = i_t - i_{t-1}$, $\Delta g_t = g_t - g_{t-1}$, $\Delta x_t = x_t - x_{t-1}$ and $\Delta m_t = m_t - m_{t-1}$ for $t = 1951, ..., 2011$. As a result, we obtain the following set of models on which the Granger causality will be explored:

$$\Delta y_t = \nu_0 + \sum_{i=1}^{n} \zeta_{0,i} \Delta y_{t-i} + \sum_{i=1}^{n} \phi_{0,i} \Delta c_{t-i} + \omega_{0,t}, \tag{5.2}$$

$$\Delta c_t = \nu_1 + \sum_{i=1}^{n} \zeta_{1,i} \Delta y_{t-i} + \sum_{i=1}^{n} \phi_{1,i} \Delta c_{t-i} + \omega_{1,t}, \tag{5.3}$$

$$\Delta y_t = \nu_2 + \sum_{i=1}^{n} \zeta_{2,i} \Delta y_{t-i} + \sum_{i=1}^{n} \phi_{2,i} \Delta i_{t-i} + \omega_{2,t}, \tag{5.4}$$

$$\Delta i_t = \nu_3 + \sum_{i=1}^{n} \zeta_{3,i} \Delta y_{t-i} + \sum_{i=1}^{n} \phi_{3,i} \Delta i_{t-i} + \omega_{3,t}, \tag{5.5}$$

$$\Delta y_t = \nu_4 + \sum_{i=1}^{n} \zeta_{4,i} \Delta y_{t-i} + \sum_{i=1}^{n} \phi_{4,i} \Delta g_{t-i} + \omega_{4,t}, \tag{5.6}$$

$$\Delta g_t = \nu_5 + \sum_{i=1}^{n} \zeta_{5,i} \Delta y_{t-i} + \sum_{i=1}^{n} \phi_{5,i} \Delta g_{t-i} + \omega_{5,t}, \tag{5.7}$$

$$\Delta y_t = \nu_6 + \sum_{i=1}^{n} \zeta_{6,i} \Delta y_{t-i} + \sum_{i=1}^{n} \phi_{6,i} \Delta x_{t-i} + \omega_{6,t}, \tag{5.8}$$

$$\Delta x_t = \nu_7 + \sum_{i=1}^{n} \zeta_{7,i} \Delta y_{t-i} + \sum_{i=1}^{n} \phi_{7,i} \Delta x_{t-i} + \omega_{7,t}, \tag{5.9}$$

$$\Delta y_t = \nu_8 + \sum_{i=1}^{n} \zeta_{8,i} \Delta y_{t-i} + \sum_{i=1}^{n} \phi_{8,i} \Delta m_{t-i} + \omega_{8,t}, \tag{5.10}$$

$$\Delta m_t = \nu_9 + \sum_{i=1}^{n} \zeta_{9,i} \Delta y_{t-i} + \sum_{i=1}^{n} \phi_{9,i} \Delta m_{t-i} + \omega_{9,t}, \tag{5.11}$$

where $\omega_{m,t}$ for $m = 1, ..., 9$ are i.i.d. error terms, ν_m for $m = 1, ..., 9$ are constants, $\zeta_{m,i}$ and $\phi_{m,i}$ for $m = 1, ..., 9$; $i = 1, ..., n$ are coefficients.

5.2 Model selection

In the thesis, we decided to execute AIC and BIC for the purpose of a model selection. Importantly, these two information criteria are widely recommended by statisticians and econometricians, as the commonly used techniques for the determination of the most desired number of independent variables (Iqbal & Uddin 2013; Maziarz 2015; Xu 2015).

For the sake of information sufficiency, we decided that AIC and BIC were executed among models 5.2–5.11 with minimum of two lags and maximum of five lags. Thus, we were examining which of the bivariate models VAR(2), VAR(3), VAR(4), VAR(5) suits the most for the purpose of Granger causality tests. Since the effect of the component variables on output is supposed to have the highest importance, the selection procedure is based only on the models where GDP serves as the dependent variable. The results from the tests are depicted in the Appendix A.1 and the consequent conclusions in the table 5.1

Overall, the most commonly chosen model was VAR(2). For example, the results of the dataset of France show, that among all components, VAR(2) is the best fitting model. Therefore, the right-hand sides of the equations 5.2 – 5.11 suited for France will always have two lags of both output and a component. The VAR(2) model was also frequently selected in datasets of Germany and Austria. Nevertheless, the AIC and BIC of these two datasets deliver in some cases different verdicts. For instance, the BIC criterion suggests VAR(2) as the best fitting model of the government expenditure for both Austria and Germany. However, the AIC concludes that the log-differenced variables Δg_t and Δy_t should contain three lags in the case of Germany and five lags in the case of Austria. In addition, the AIC selected the number of four lags as the most sufficiently fitting to the model of German import.

Table 5.1: Determination of the models and Granger causality tests

Variable	Unit root	Coint.	AIC	BIC	$y_t \rightarrow x_t$	$x_t \rightarrow y_t$
Austria						
y_t	I(1)					
c_t	I(1)	No	VAR(2)	VAR(2)	0.0024	0.6241
i_t	I(1)	Yes	VEC(2)	VEC(2)	0.0067	0.0509
g_t	I(1)	No	VAR(5)	VAR(2)	0.0537; 0.3851	0.0003; 0.0381
x_t	I(1)	No	VAR(2)	VAR(2)	0.0376	0.0623
m_t	I(1)	No	VAR(2)	VAR(2)	0.0125	0.0102
France						
Variable	Unit root	Coint.	AIC	BIC	$y_t \rightarrow x_t$	$x_t \rightarrow y_t$
y_t	I(1)					
c_t	I(1)	No	VAR(2)	VAR(2)	0.0048	0.0187
i_t	I(1)	No	VAR(2)	VAR(2)	0.0165	0.0429
g_t	I(1)	No	VAR(2)	VAR(2)	0.2573	0.0002
x_t	I(1)	No	VAR(2)	VAR(2)	0.4143	0.6486
m_t	I(1)	No	VAR(2)	VAR(2)	0.0385	0.0153
Germany						
Variable	Unit root	Coint.	AIC	BIC	$y_t \rightarrow x_t$	$x_t \rightarrow y_t$
y_t	I(0)					
c_t	I(1)	No	VAR(2)	VAR(2)	0.0141	0.1205
i_t	I(1)	No	VAR(2)	VAR(2)	0.0101	0.0675
g_t	I(1)	No	VAR(3)	VAR(2)	0.0751; 0.1643	0.0007; 0.0003
x_t	I(0)	No	VAR(2)	VAR(2)	0.5788	0.2916
m_t	I(0)	No	VAR(4)	VAR(2)	0.0185; 0.2534	0.0532; 0.4121

Source: Stata 12 and author's conclusions

Note: The last two columns depict p-values from the Granger causality tests. The variable x_t represents the component variable which is defined in the certain row.

5.3 Unit root tests

Next, the vital testing procedure is the determination of the order of integration of the variables. In other words, we have to decide whether the stochastic processes are I(0) or I(1), respectively. For the sake of correct statistical inference, if we found no evidence for or against a unit root in two variables, there is a "danger" of cointegration between them. Therefore, the DF and ADF test should be executed on GDP and its components. Moreover, all of the variables are time-trending over time. The significance of a time trend is ascertained in the regressions, where the only regressor is the time variable *"year"* (Appendix A.2, A.3 and A.4). As a consequence, the variables in levels were subjects of DF and ADF tests with a time trend. The results of the tests can be seen in the Appendix A.5 and the conclusions in the table 5.1. We were concluding at the 5% level of significance.

The results indicates that a unit root cannot be rejected in most of the variables. Overall, we have evidence for a process to be I(0) only in two cases in the dataset of Germany — output and export. As a result, the variables of France and Austria have to undergo further tests for cointegration. Generally, we are interested whether output is cointegrated with some of its components. If so, the underlying VAR model should be adjusted for the error correction term. Nonetheless, testing for cointegration in the dataset of Germany is not necessary, since we found evidence for the German GDP to be I(0) process. The latter conclusion implies from the already mentioned equivalence: two stochastic processes can be cointegrated if and only if both are integrated of order one (Wooldridge 2013). Therefore, the cointegration between output and its components is statistically possible only in cases of Austria and France. As in the DF and AFD test, the test for cointegration needs to be controlled for a time trend. The results of the test are depicted in the Appendix A.5 and the conclusions in the table 5.1.

As for the results, at 5% significance level we conclude that there is no cointegration between output and its components, except for one case in the Austrian dataset. Namely, we found evidence for the linear combination of output and investment of Austrian economy to be stationary I(0) process. In other words, investment and output in Austria move together in a long-run relationship. Consequently, the VAR(2) models 5.4 and 5.5 need to be adjusted for the error correction terms, which would control for the long-run relationship.

5.4 Granger causality tests

To move on, the main objective of the thesis is to examine forecasting capability of the components on GDP. Green (1997) contends that the test for Granger causality ought to be executed on a model with stationary variables. We demonstrated that all of the variables are non-stationary, because they are driven by a deterministic trend. Moreover, we found evidence that some of the variables are driven by a stochastic trend, too. Nevertheless, the models 5.2 – 5.11 are written in first log-differences and therefore the variables Δy_t, Δc_t, Δi_t, Δg_t, Δx_t and Δm_t are stationary I(0) processes, which are not influenced by a trend.

What is more, Green (1997) claims that cointegration between two variables, which were put into log-differences and then included in a VAR model, would cause incorrect statistical inference of the Granger causality test. For that reason, VAR model would cease to be valid for the purpose of causality testing, which means that it is replaced by VEC.

Overall, due to above mentioned testing procedures we selected thirty six models from three countries on which Granger causality will be examined. In addition, twenty eight models are VAR(2), six models are either VAR(3) or VAR(4) or VAR(5) and the remaining two models are VEC(2). As implies by the F- statistics 3.5, VAR(2) and VECM(2) have $F(2, 54)$ distribution, VAR(3) has $F(3, 51)$ distribution, VAR(4) has $F(4, 48)$ distribution and finally VAR(5) has $F(5, 45)$ distribution. The p-values corresponding with the particular distribution of the selected model are depicted in the table 5.1.

5.4.1 Results

As for the results, the null of no Granger causality was rejected eight times in total at 1% significance level. In the Austrian economy, we concluded that at 1% significance level consumption Granger-causes output but not *vice versa*.

Moreover, we found that investment Granger-causes output but no *vice versa*at 1% significance level. On the contrary, we found evidence that at 1% significance level output Granger-causes government expenditures contained in VAR(5) model, however it does not hold the other way around.

As for the economy of Germany, at 1% significance we can conclude that output Granger-causes government expenditures. The latter holds for both VAR(2) and VAR(3) model. Nevertheless, the null of no Granger causality of government expenditures on output failed to be rejected, therefore there is no reciprocal causality between Δy_t and Δg_t.

When it comes to France, the results are similar to the Austrian economy. At 1% significance level we conclude that consumption and investment Granger-cause GDP, but not *vice versa*. In contrast, we found evidence for government expenditures being Granger-caused by output, but again it does not hold the other way around.

After adjusting the level of significance to 5%, the conclusions become slightly different. In the Austrian dataset, we found evidence for reverse Granger causality of output and investment. In addition to results of tests at 1% significance level, at 5% significance level we can conclude that output Granger-causes government expenditures contained in both VAR(2) and VAR(5) models. What is more, we can draw conclusions that export Granger-causes output, however not *vice versa*. When it comes to import, there is evidence of reciprocal Granger causality.

Furthermore, the estimation of mutual Granger causality of output and investment in Austria was based on VEC(2) model. However, under the assumption of no cointegration between these two variables we can execute the test to original VAR(2) model. As a result, we obtained p-value 0.0067 from the Granger causality test of investment on output. On the contrary, the p-value of the Granger causality test of output on investment is 0.0509. Thus, we have no longer evidence for reciprocal causality, nevertheless output remains being Granger-caused by investment at 1% significance level.

As for the data of Germany, at 5% significance level we rejected the null of no Granger causality of consumption and investment on output, hence we conclude that variables Δc_t and Δi_t Granger-cause the variable Δy_t. In addition, we found evidence for output being Granger-caused by import, but this inference holds only for tests based on the VAR(4) model.

When it comes to the dataset of France, at 5% significance level we found evidence for three reciprocal Granger causalities. Namely, we concluded that investment, consumption and import Granger-cause output and *vice versa*.

To sum up, these three datasets show slightly different results, however there is visible a common pattern encompassed in all three countries. As a matter of the research, investment and consumption Granger-cause output. In contrast, output Granger-causes government expenditures.

To conclude with, in accordance with the Granger causality approach, we found evidence that consumption and investment have forecasting capability on

GDP. On the contrary, we infer that GDP has capability to forecast government expenditures. When it comes to import and export, there is no such common pattern encompassed in the economies.

5.5 Granger causality in panel data

After exploring the separate causal relationships between GDP and its components in three European countries, we are interested how the data would behave in a single macro-panel. As written above, there are several advantages in using a panel. The most straightforward is increasing of the number of observations. Hence, we put Austria, France and Germany data together. As a result, we obtained the dataset with 186 observations in total.

In general, we applied the similar testing procedure as in separate datasets. We transformed all of the variables into natural logarithm and then we put the levels into first-differences. Naturally, each step was done with respect to the macro-panel data. Overall, the set of tested equations remains the same (5.2 – 5.11), however with further adjustment to the cross-sectional units. For the sake of illustration, the indexes determining the countries (see: section 4.4) were added to the equations 5.2 – 5.11.

As for the disadvantage of having a panel, the statistical inference is might be incorrect due to heterogeneity bias. Nevertheless, under the log-transformation and succeeding first-differencing, the fixed effect is controlled for.

As before, the statistical inference in incorrect under cointegration of two variables. Therefore, we need to examine the order of integration of the panel variables $y_{k,t}$ and $c_{k,t}$, where k determines the number of cross-sectional units (which is number 3 in our case). For that reason, we run the unit root test for panel data, introduced by Levin *et al.* (2002). The test is similar to the DF and ADF, however with further respect to cross-sectional dependencies in a panel. The p-values from the test are depicted in the Appendix A.6. Naturally, the test was adjusted for a time trend.

As for the results, at 5% significance level we can conclude that variables of output, investment, consumption and are I(0) processes. On the contrary, variables of government expenditures and export are I(1) processes. As a consequence, there is statistically no need for further cointegration tests. Therefore, the Granger causality tests are applied on original VAR models.

As a matter of previous empirical evidence, AIC and BIC criteria frequently selected VAR(2) as the best fitting model. For that reason, we decided to apply VAR(2) to all the tests for causal relationship within the panel. Hence, the underlying F-statistics has asymptotically $F(2, 162)$ distribution and the corresponding p-values are depicted in the table A.7 (Appendix).

As for the results, at 1% significance level we conclude that consumption Granger-causes output, but not *vice versa*. On the contrary, output Granger-causes government expenditures. In addition, investment with output and import with output are found to have mutual causal relationship.

Overall, the ascertained pattern is distinguishable in the macro-panel, too. We found evidence that consumption and investment incorporate forecasting capability on GDP. In contrast, output has been found to have ability to forecast government expenditures. To conclude with, the pattern, which was separately shown by the datasets of three member states of the European Union, is visible in the composite context, too.

5.6 Actual performance of the selected variables

In this part, we are going to demonstrate the concrete behaviour of the variables, which were found to have the highest predictive ability. We will demonstrate how exactly the particular variable is influential in the causal relationship, which was tested above. Namely, we concluded that investment and consumption have forecasting capability on GDP, while GDP has ability to predict government expenditures. Overall, we are interested in the impact of one variable to another over short and long time horizon. In simple words, we are going to demonstrate the short run and long run effect of consumption and investment on income and short run and long run effect of GDP on government expenditures.

5.6.1 Impact multiplier and long-run multiplier

The short run effect determines the impact of one variable on another within the short period of time. In the thesis, we are going to estimate short run effects of the variables defined in the same year. If we are speaking about the long run effect, we will mean the impact of one variable on another over some unspecified long time period. Wooldridge (2013) describes the way of estimating the effects on the model which is defined as follows:

$$z_t = a_5 + \sum_{i=0}^{p} b_{5,i} x_{t-i} + e_{5,t}, \tag{5.12}$$

where $e_{5,t}$ is i.i.d. error term, a_5 is a constant and b_i for $i = 0, ..., p$ are coefficients. Obviously, the FDL model 5.12 assumes that the dependent variable z_t is explained by p lags of the variable x_t and also by variable x_t itself.

As mentioned before, the short run effect is the impact of one variable on another within the same year. As implies by the FDL model, the effect is determined by the coefficient by the variable x_t. As for appellation, this constant is called *impact multiplier*. In contrast, the *long-run multiplier*, which determines the impact over long period of time, is the cumulative sum of all individual effects in the course of time. For the sake of clarity, the long run multiplier is the sum of all coefficients b_i for $i = 0, ..., p$.

Nevertheless, if lagged values of dependent variable are included among regressors, the computation of the long run multiplier is more complicated. Obviously, the lagged value of the dependent variable has self-contained information about the whole model. Accordingly, Wooldridge (2013) proposes a simple technique for long run effect determination. The long run equilibrium is ascertained by deleting time indexes of all variables. As for demonstration, imagine the following model:

$$z_t = a_0 + b_1 z_{t-1} + b_2 x_t + b_3 x_{t-1} + b_4 t + e_t, \tag{5.13}$$

where e_t is i.i.d. error term, a_0 is a constant and b_1, b_2, b_3, b_4 are coefficients and t is a time variable. In accordance with the above proposed computation, the long run multiplier is therefore established in the following way:

$$z* = a_0 + b_1 z* + b_2 x* + b_3 x* + b_4 t + e_t, \tag{5.14}$$

$$z* = \frac{a_0}{1 - b_1} + \frac{b_2 + b_3}{1 - b_1} x* + \frac{b_4 t}{1 - b_1} + \frac{e_t}{1 - b_1}, \tag{5.15}$$

where the coefficient $\frac{b_2+b_3}{1-b_1}$ (for $b_1 \neq 1$) by the variable $x*$ stands for the intended long run effect.

For the purpose of this exercise, we decided to demonstrate the impact multiplier and long run multiplier on the model 5.13. Clearly, we assume that in addition to the variables x_t and x_{t-1}, the dependent variable is also explained by its lagged value and the time variable t. For the sake of clarity, we rewrite the model 5.13 as:

$$z_t^{(m)} = a_0 + b_1 z_{t-1}^{(m)} + b_2 x_t^{(m)} + b_3 x_{t-1}^{(m)} + b_4 t + e_t, \tag{5.16}$$

where $m = 1, 2, 3$.

If $k = 1$, the dependent variable z_t stands for output and the independent variable x_t for consumption. Therefore, under $k = 1$, we examine the effects of consumption on output over two time horizons: short run and long run. If $k = 2$, the dependent variable z_t stands for output and independent variable x_t for investment. Finally, if $k = 3$, the dependent variable z_t stands for government expenditures and the independent variable x_t for output. Overall, the particular pair of variables being examined is in logical accordance with the findings in the section 5.4.1.

We estimated the multipliers in the datasets of Austria, France and Germany separately. Furthermore, we used the same computing method for the macro-panel dataset, too. The equation 5.13 in the panel was estimated by the fixed effect model. The underlying regressions can be seen in the Appendix A.8, A.9, A.10 and A.11. The conclusions are depicted in the table 5.2.

In consideration of the regressions, the income models of investment and consumption have always individually significant (at 5% significance level) the particular GDP component variable. Nevertheless, it does not hold for the government expenditure models, where output and its lagged value are in some cases insignificant. Nevertheless, each regressions shows that all of the independent variables are jointly significant.

As for the Austrian economy, we conclude that in short run, 1% increase in consumption results in 0.75% increase in income and 1% increase in investment in 0.187% increase in income. When it comes to the long run effect, permanent 1% increase in consumption causes GDP to rise by 0.845%. Moreover, permanent 1% increase in investment rises output by approximately half percentage point. In regards to the influence of GDP, 1% increase in output results in 0.13% increase of government expenditures in short-run, and 0.63% in long-run. The broadest difference between impact multiplier and long run multiplier was estimated with respect to government expenditures. Moreover, we concluded that in long run consumption has the highest impact on income.

In reference to Germany, there is almost no difference over time horizon between the effects of consumption. As a result, 1% rise in consumption causes

Table 5.2: Impact multipliers and long run multipliers

Austria		
Effect	Impact	Long run
c_t on y_t	0.752	0.845
i_t on y_t	0.187	0.513
y_t on g_t	0.134	0.639
France		
Effect	Impact	Long run
c_t on y_t	0.938	1.134
i_t on y_t	0.224	1.013
y_t on g_t	-0.011	1.141
Germany		
Effect	Impact	Long run
c_t on y_t	0.725	0.745
i_t on y_t	0.251	0.516
y_t on g_t	-0.132	0.712
Panel		
Effect	Impact	Long run
c_t on y_t	0.793	0.739
i_t on y_t	0.212	0.605
y_t on g_t	0.091	0.988

Source: Stata 12

approximately 0.75% increase in income. As for investment, the long-run multiplier of is twice as the impact multiplier. Interestingly, 1% increase in output is estimated to decrease government expenditures by -0.13%. Nonetheless, the coefficient is not statistically significant, therefore we are more interested in the long run multiplier, which is 0.711.

Interestingly, the dataset of France shows, that permanent rise in either consumption or investment increases GDP more than once. Moreover, the long-run multiplier of output with respect to government expenditures is more than unity, too.

Taking into account the macro-panel, the inference is not far from the separate findings. We conclude that consumption has generally higher impact on GDP than investment. The permanent 1% increase in either consumption or investment increases output by more than half a percentage point. However, due to individual insignificance of coefficients, a little statistical emphasis is put on the impact of output on government expenditures in short run. Nevertheless, we can draw conclusion about the long run multiplier, which is estimated to be equal almost to unity.

5.7 Discussion

Finally, we would like to compare our findings with the academic surveys in the section 2.2.2. To some extent, our conclusions are in accord with the findings of Narayan & Smyth (2008) and Tiwari (2014). The authors detected that energy consumption Granger-causes income. Finally, we would like to compare our findings with the academic surveys in the section 2.2.2. To some extent, our conclusions are in accord with the findings of Narayan & Smyth (2008) and Tiwari (2014). The authors detected that energy consumption Granger-causes income. Moreover, Narayan & Smyth (2008) computed long run effect of energy consumption on GDP which was estimated to be between 0.12% and 0.39%. Comparing to our results, we demonstrated that the long run multiplier of total consumption on income with respect to panel data is 0.73%.

As for investment, our results contradict the findings of Kumar Narayan & Smyth (2006), who found evidence for real investment being Granger-caused by real output. In contrast, in this thesis we drew reverse conclusion. Nevertheless, our verdicts are to some extent in consensus with Green (1997), who discovered the unidirectional causal relationship of residential investment and output.

Cheng & Lai (1997) concluded that there is reciprocal causal relationship between GDP and government expenditures. According to our research, we found evidence for only unidirectional causality. In particular, we ascertained that real GDP has ability to forecast government expenditures.

In consideration of import and export, Ming-Hsien *et al.* (2015) discovered that within the Chinese and Taiwanese economies the causal relationship between export and GDP is mutual. On the contrary, we found no evidence for or against the null hypothesis of no Granger causality between export and output, hence we concluded that in the European context these two variables are not causally linked. As for import, Todshki & Ranjbaraki (2016) found evidence for steel import being Granger-caused by GDP. To compare with our results, the dataset of Germany partly authenticates the same conclusion. Nonetheless, table A.7 in Appendix infer that the causal relationship between import and GDP is in general mutual, too.

However, it is vital to mention that the authors in the section 2.2.2 devoted to the question of Granger-causality with respect to GDP expenditure approach only partly. In general, they focus mostly on a certain part of the component variables. On the other hand, this thesis aims to provide the general procedure to determine the ability of five national account variables to forecast economic growth.

On the whole, the thesis exemplifies the bivariate analysis of the Granger's method. As for the further research suggestion, the Xu (2015) elaborates the original Granger causality test by augmenting the number of tested variables. As a consequence, the examining causal relation is based on multivariate analysis. According to his methodology, a potential study can be aimed at exploring causality among three or more variables within the expenditure approach of GDP calculation.

Chapter 6

Conclusion

In this thesis we were exploring forecasting capability of GDP components, which were selected in accordance with the expenditure approach of output computation. On the whole, the research is based on the Granger's testing procedure of bivariate causal relationship.

For the purpose of this research, we decided to examine the Granger's causality with the aid of a VAR model. For the sake of correct statistical inference, the variables used within the testing procedure were log-differenced. Nevertheless, the literature mentioned in the chapter 3 claims that cointegration between dependent and independent variables in the vector auto-regression results in biased conclusions about causal relationship. Therefore, if the linear combination of GDP and its component is found to be a I(0) stochastic process, the error correction term is added to the regression. Furthermore, the optimal number of lags included in the model were selected in accordance with the Akaike information criterion and the Bayesian information criterion. Overall, the chapter 3 provides the complex procedure of preliminary tests and appropriate model determination.

As for the empirical part, we collected datasets of national account variables of three European countries: Austria, France and Germany. Overall, we concluded that consumption and investment evince capability to forecast changes in output. In contrast, GDP was found to have forecasting ability on government expenditures. As for import and export, there was no general pattern showed by the separate datasets. Nevertheless, data of Austria and France show evidence for reciprocal causal relationship between income and export.

In addition, we decided to explore whether the pattern determined in the separate datasets will be visible in a composite macro-panel, too. Therefore, we put these three countries together and executed the preliminary tests, however with respect to panel data estimators. As a result, the detected evidence supported the above findings, therefore we conclude that the pattern, which was separately shown by the datasets of three member states of the European Union, is visible in the composite context, too.

In the section 5.6 we examined the concrete behaviour of the selected component variables. In general, we demonstrated how exactly the particular variable was influential in the causal relationship, which had been tested in the previous sections. Regarding the results, we concluded that consumption has higher impact on GDP that investment. In the context of the macro-panel, permanent 1% increase in consumption results in 0.73% increase in output. Furthermore, the long run multiplier of income on government expenditures was generally almost equal to unity.

To conclude with, the thesis does not tend to serve as a complex elaboration of the topic of causality. The author endeavours to demonstrate a potential procedure for determining whether one variable could be useful in forecasting other variable. Overall, the presented study remains open to further augmentation and sophistication. For instance, a potential research can be aimed at multivariate approach of the above described analysis.

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Appendix A

Appendix

Table A.1: AIC and BIC statistics

		Austria		
VAR of GDP and:	VAR(2)	VAR(3)	VAR(4)	VAR(5)
Consumption	-288.3049; -277.9172	-280.0794; -265.6563	-271.8587; -253.4713	-270.1214; -247.8425
Investment	-286.0433; -275.6556	-277.2858; -262.8627	-272.6348; -254.2474	-268.6047; -246.3259
Government exp.	-277.1819; -266.7943	-273.0559; -258.6328	-268.1764; -249.7889	-279.7667; -257.4879
Export	-282.2656; -271.8779	-274.7592; -260.3361	-267.0839; -248.6964	-272.8810; -250.6021
Import	-284.6684; -274.2807	-279.7610; -265.3379	-275.6216; -257.2341	-272.7294; -250.4505
		France		
VAR of GDP and:	VAR(2)	VAR(3)	VAR(4)	VAR(5)
Consumption	-316.7346; -306.3469	-308.1283; -293.7052	-298.9648; -280.5774	-291.0062; -268.7273
Investment	-314.0542; -303.6665	-307.3492; -292.9261	-297.2928; -278.9054	-287.7283; -265.4494
Government exp	-308.0506; -297.6629	-301.9354; -287.5123	-295.0328; -276.6453	-285.6422; -263.3633
Export	-307.0091; -296.6215	-299.5808; -285.1577	-290.6424; -272.2550	-281.5997; -259.3208
Import	-312.2036; -301.8159	-304.6637; -290.2406	-295.692; -277.3045	-286.8044; -264.5256
		Germany		
VAR of GDP and:	VAR(2)	VAR(3)	VAR(4)	VAR(5)
Consumption	-280.0512; -269.6635	-276.1597; -261.7366	-272.9358; -254.5483	-278.5127; -256.2338
Investment	-280.7951; -270.4075	-274.6063; -260.1832	-275.2009; -256.8134	-268.7671; -246.4882
Government exp	-274.6927; -264.3050	-275.5876; -261.1645	-271.7140; -253.3265	-266.6412; -244.3624
Export	-271.9409; -261.5532	-269.2832; -254.8601	-268.2324; -249.845	-267.2999; -245.0211
Import	-273.7458; -263.3581	-270.9099; -256.4868	-279.7735; -261.386	-271.6602; -249.3814

Source: Stata 12

Note: The inserted values are depicted in the following order: AIC; BIC

Table A.2: Significance of time trend — Austria

	(1) y	(2) c	(3) i	(4) g	(5) x	(6) m
year	0.0325***	0.0310***	0.0345***	0.0257***	0.0650***	0.0612***
	(0.000815)	(0.000928)	(0.00144)	(0.000437)	(0.00142)	(0.00167)
_cons	-52.57***	-50.19***	-58.07***	-40.76***	-118.4***	-111.0***
	(1.615)	(1.837)	(2.849)	(0.865)	(2.816)	(3.311)
N	62	62	62	62	62	62

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.0001$

Table A.3: Significance of time trend — France

	(1) y	(2) c	(3) i	(4) g	(5) x	(6) m
year	0.0321***	0.0310***	0.0324***	0.0333***	0.0605***	0.0604***
	(0.000996)	(0.000893)	(0.00151)	(0.000901)	(0.00123)	(0.00124)
_cons	-49.89***	-48.31***	-52.21***	-53.69***	-108.1***	-108.0***
	(1.973)	(1.769)	(2.994)	(1.785)	(2.427)	(2.448)
N	62	62	62	62	62	62

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.0001$

Table A.4: Significance of time trend — Germany

	(1) y	(2) c	(3) i	(4) g	(5) x	(6) m
year	0.0299***	0.0311***	0.0249***	0.0282***	0.0624***	0.0641***
	(0.00109)	(0.00121)	(0.00138)	(0.00113)	(0.00121)	(0.00169)
_cons	-45.17***	-48.04***	-36.82***	-43.37***	-111.4***	-114.8***
	(2.158)	(2.398)	(2.725)	(2.228)	(2.398)	(3.350)
N	62	62	62	62	62	62

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.0001$

Table A.5: Statistics from DF, ADF and cointegration tests

Austria			
Variable	DF	ADF	Coint.
y_t	-1.256	-1.253	
c_t	-1.232	-1.709	-2.892
i_t	-1.881	-1.716	-4.474
g_t	0.015	-0.156	-2.503
x_t	-2.515	-3.075	-2.800
m_t	-1.544	-1.774	-3.679
France			
Variable	DF	ADF	Coint.
y_t	-0.186	-0.474	
c_t	-0.829	-0.529	-3.255
i_t	-1.678	-1.841	-1.000
g_t	0.912	0.290	-1.825
x_t	-0.066	-0.481	-3.154
m_t	-0.993	-0.835	-2.670
Germany			
Variable	DF	ADF	Coint.
y_t	-4.525	-3.639	
c_t	-2.908	-2.607	not tested
i_t	-3.021	-3.416	not tested
g_t	-2.767	-1.974	not tested
x_t	-4.698	-3.839	not tested
m_t	-2.380	-4.494	not tested

Source: Stata 12

Table A.6: Unit root test in the panel

Panel	
Variable	p-value
$y_{k,t}$	0.0223
$c_{k,t}$	0.0085
$i_{k,t}$	0.0134
$g_{k,t}$	0.6374
$x_{k,t}$	0.0571
$m_{k,t}$	0.0003

Source: Stata 12

Table A.7: Granger causality test in the panel (p-values)

Panel		
Variable	$y_{k,t} \rightarrow x_{k,t}$	$x_{k,t} \rightarrow y_{k,t}$
$y_{k,t}$		
$c_{k,t}$	0.00	0.0847
$i_{k,t}$	0.00	0.00
$g_{k,t}$	0.0972	0.00
$x_{k,t}$	0.5689	0.0546
$m_{k,t}$	0.0015	0.00

Source: Stata 12

Note: The variable $x_{k,t}$ represents the component variable which is defined in the certain row.

Table A.8: Regression — Austria

	(1)	(2)	(3)
	y	y	g
y_1	0.761***	0.880***	-0.0325
	(0.103)	(0.0643)	(0.0977)
c	0.752***		
	(0.123)		
c_1	-0.550***		
	(0.122)		
year	0.00142*	0.00125	0.000536
	(0.000757)	(0.000965)	(0.000741)
i		0.187***	
		(0.0312)	
i_1		-0.125**	
		(0.0310)	
g_1			0.842***
			(0.0604)
y			0.134*
			(0.0770)
_cons	-2.270*	-1.677	-0.617
	(1.233)	(1.489)	(1.154)
N	61	61	61
F	14018.1	30775.0	16163.2

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.0001$

Table A.9: Regression — France

	(1)	(2)	(3)
	y	y	g
y_1	0.774***	0.955***	0.156
	(0.109)	(0.0142)	(0.141)
c	0.938***		
	(0.131)		
c_1	-0.682***		
	(0.0918)		
year	-0.000797*	-0.000609**	-0.00108**
	(0.000412)	(0.000261)	(0.000366)
i		0.224***	
		(0.0129)	
i_1		-0.178***	
		(0.0151)	
g_1			0.874***
			(0.0286)
y			-0.0114
			(0.138)
_cons	1.307**	1.298**	1.740**
	(0.644)	(0.401)	(0.556)
N	61	61	61
F	34352.4	92960.6	31547.5

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.0001$

Table A.10: Regression — Germany

	(1)	(2)	(3)
	y	y	g
y_1	0.762***	0.901***	0.236**
	(0.0889)	(0.0230)	(0.108)
c	0.725***		
	(0.108)		
c_1	-0.548***		
	(0.105)		
year	0.00135**	0.000896**	-0.000123
	(0.000432)	(0.000361)	(0.000609)
i		0.251***	
		(0.0259)	
i_1		-0.200***	
		(0.0283)	
g_1			0.854***
			(0.0420)
y			-0.132
			(0.110)
_cons	-1.714**	-0.996*	0.635
	(0.726)	(0.557)	(0.878)
N	61	61	61
F	28098.6	45723.4	10687.2

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.0001$

Table A.11: Regression — Panel

	(1)	(2)	(3)
	y	y	g
y_1	0.925**	0.908**	-0.0114
	(0.0221)	(0.0258)	(0.0712)
c	0.793**		
	(0.0277)		
c_1	-0.737**		
	(0.0396)		
year	0.000508	0.000550	-0.000749
	(0.000489)	(0.000609)	(0.000489)
i		0.212**	
		(0.0236)	
i_1		-0.156**	
		(0.0224)	
g_1			0.919**
			(0.0297)
y			0.0910
			(0.0617)
_cons	-0.710	-0.499	1.398
	(0.746)	(0.942)	(0.694)
N	183	183	183
F	.	.	.

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.0001$